Type-based MCMC for Sampling Tree Fragments from Forests

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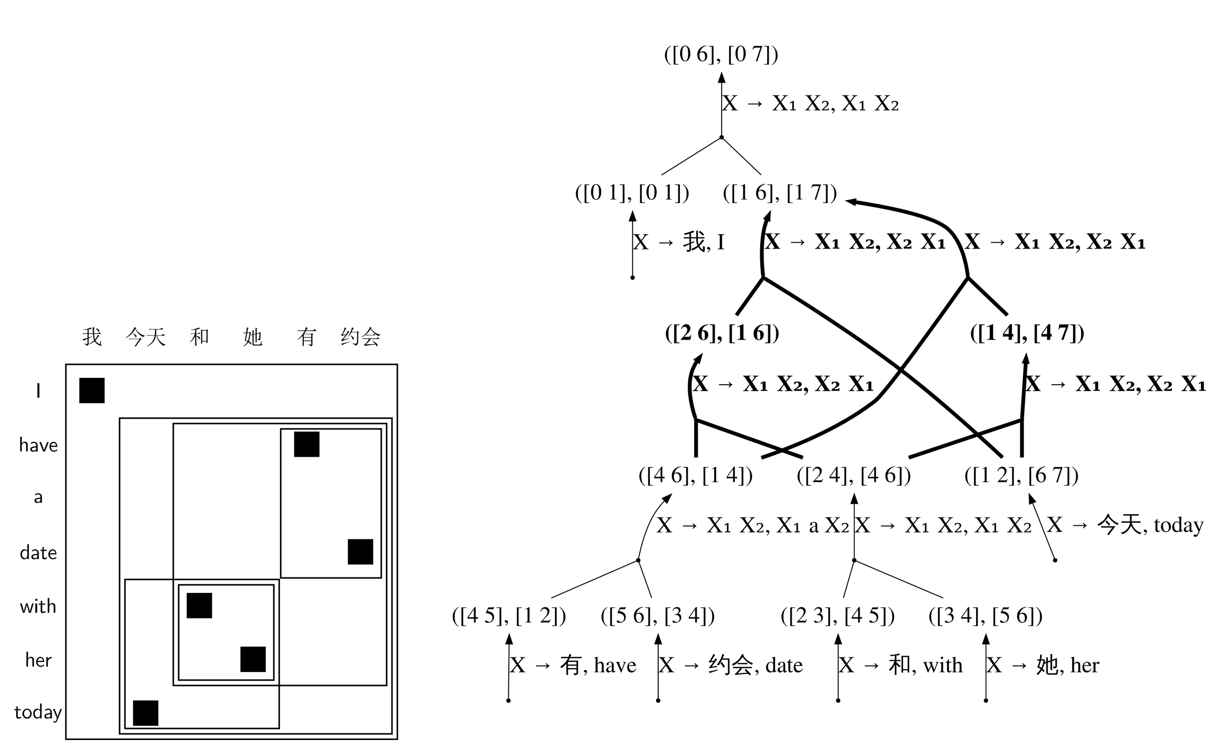
Overview

- We apply type-based MCMC to learning SCFG rules.
  - Assume fixed word alignment.
  - Learn SCFG rules consistent with alignment, each SCFG rule is a tree fragment in the phrase decomposition forest.
  - We assume fragment sizes (as in TSG learning) as well as bracketing structures (extending TSG learning)
- We investigate the impact of type-based method on the likelihood of the Markov Chain in this setting.
  - Token-based and block-based MCMC: do not deal with the coupling issue of variables.
  - Type-based MCMC: grouping strongly coupled variables as the same type.
- We present an innovative way of storing the type information.
  - Reduce the amount of bookkeeping by indexing on partial type information.
  - Additional steps to filter nodes with full type information.
- We replace the two-stage sampling schedule of Liang et al. (2010) with a simpler and faster one-stage method.
- Parallel programming with inexact type-based MCMC

Sample Tree Fragments from Forests

- Chung et al. (2014) present a schedule to learn Hiero-style SCFG rules from phrase decomposition forests
  - Build a phrase decomposition forest from bottom up
  - MCMC sampling from top down: sample cut, sample edge.



Type-based MCMC

- Two cut sites are of the same type if the composed rules we get are exactly the same when assigning same cut value to them:

$$type(t, n) \stackrel{\text{def}}{=} (r_1, r_2, r_3)$$

- We calculate the joint probability of an assignment having m cut sites:

$$P(z_S|N) \propto \prod_{i=1}^{n-m} P(r_1|N^{i-1}) \prod_{i=1}^{m} P(r_2|\bar{N}^{i-1}) P(r_3|\hat{N}^{i-1}) \stackrel{\text{def}}{=} g(m)$$

- The posterior probability of all assignments having m cut sites is:

$$p(m|N) \propto \sum_{z_S: m=\sum_i z_i} p(z_S|N) = \binom{n}{m} g(m)$$

- We sample m according to this equation. Then we choose m sites among the n variables to be cut with uniform distribution.

Bookkeeping Strategy

- Unlike PTSG: the internal structure of each rule type is abstracted away.
- Strategy: build a small index at the cost of additional computation:
  - We only key on the rule types turned on in the current chosen derivation
  - We key on a single rule type and index only the root of each rule type

Optimization

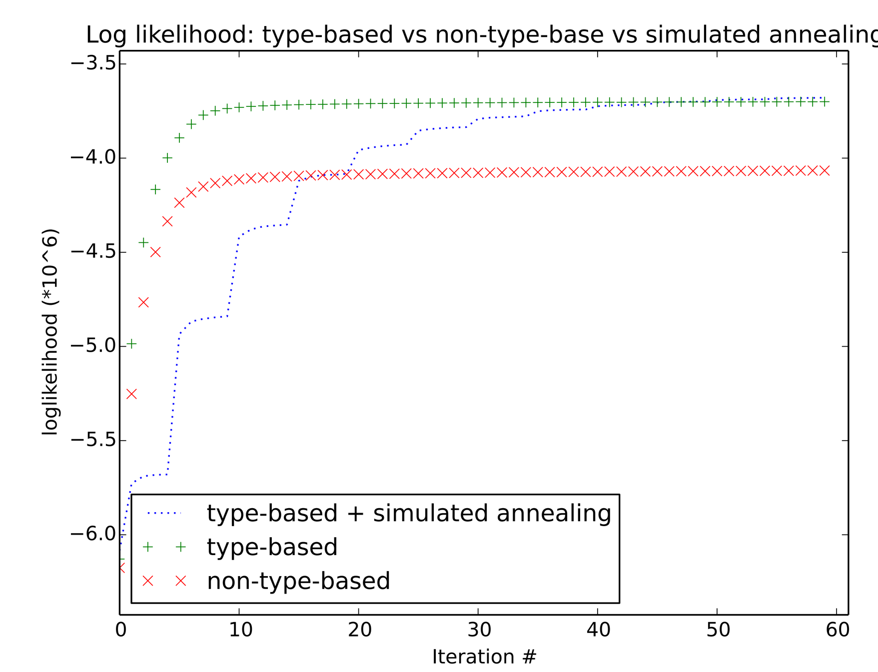
- One-stage sampling schedule: build real m greedily.

$$P(z_S|N) = \prod_{i=1}^{n} P(z_i|N^{i-1})$$

- Inexact type-based MCMC with parallel programming:
  - Split the data into subsets, communicate local counts.
  - The local bookkeeping of each subset is not communicated.

Experimental Results

- Type-based sampling converges to a much better result than non-type-based top-down sampling and escapes some local optima that are hard for token-based methods to escape:



- The better likelihood of our Markov Chain using type-based MCMC also results in better translation:

Sampling Schedule	iteration	dev	test
Non-type-based	averaged (0-90)	25.62	24.98
Type-based	averaged (0-100)	25.88	25.20
Parallel Type-based	averaged (0-90)	25.75	25.04

- When using a parallel programming approximation, the likelihood finally converges to the same likelihood result as non-parallel type-based MCMC: